Working Paper:

Effects of the American Fisheries Act on the Harvesting Capacity, Capacity Utilization, and Technical Efficiency of Pollock Catcher-Processors

by
Ron Felthoven
National Marine Fisheries Service
Alaska Fisheries Science Center
7600 Sand Point Way, Seattle WA 98115

Abstract

The American Fisheries Act (AFA) of 1998 significantly altered the Bering Sea and Aleutian Islands pollock fishery by allowing the formation of harvesting and processing cooperatives and defining exclusive fishing rights. This paper uses data envelopment analysis and stochastic production frontier models to examine effects of the AFA on the fishing capacity, technical harvesting efficiency (TE), and capacity utilization (CU) of pollock catcher-processors. The results indicate that fishing capacity fell by more than thirty percent and that harvesting TE and CU measures increased relative to past years. This work provides examples of how existing data, which is currently devoid of operator costs and provides only general indicators of earnings, may be used to analyze changes in elements of fleet and vessel performance in response to management actions.

I. Introduction

The American Fisheries Act (AFA) of 1998 significantly changed the nature of the offshore Alaskan pollock fishery by removing nine catcher-processors from the fishery and allowing the formation of a cooperative structure among the remaining participants -- essentially eliminating the longstanding race for fish. These changes have facilitated longer seasons, greater product recovery rates, increased product quality, and a heightened ability to react to both market signals when choosing product forms and to regulations regarding Stellar sea lions restrictions. As a result, there are many areas where economic analysis of the effects of the AFA would be quite informative. However, the economic data currently available to NMFS staff to analyze such changes is quite limited.

The purpose of this paper is to illustrate ways in which existing data may be used to analyze changes in fleet and vessel performance resulting from implementation of the AFA (or other management actions). In particular, this work examines how changes in annual catch have compared to changes in harvesting effort, vessel participation, and stock abundance – providing estimates of technical harvesting efficiency (TE) and capacity utilization (CU). Using these results, and by focusing on the pollock catcher-processors in particular, we also generate measures of fishing capacity and examine how it changed in response to vessel buyouts and the introduction of fishing rights under the cooperative structure.

Due to the current absence of data regarding vessel costs and earnings, the models used to estimate fishing capacity for the pollock catcher-processors are based primarily on annual catch levels and the inputs and effort used to generate them. Such models are referred to as "primal", as they are aimed only at representing production relationships and not the behavioral responses to market prices. It should be noted at the outset that primal measures of capacity do not directly assess the economic "optimality" of a particular fleet size. Rather, the estimates indicate the maximum output that could be produced with the observed fixed factors of production, resource stock, state of technology, etc. Still, an assessment of how such levels have changed over time provides information regarding the catching power of the fleet, how it compares to actual catch, and on the likelihood of excess capacity existing in the fishery[1].

[1] For example, if potential catch is many times greater than actual catch, then in many cases one could likely conclude that there is excess capacity in a fishery, even without information on costs or an economic assessment of the "optimal" fleet size.

In the work that follows, two methodologies (data envelopment analysis [DEA] and stochastic production frontiers [SPF]) recently suggested by academics participating in the NMFS-organized Expert Panel on Fish Harvesting Capacity Metrics are used to construct estimates of harvesting capacity. Both of the approaches are employed in order to illustrate two potential techniques and to gauge the robustness of the findings to model specification[2]. While the models differ somewhat in the way they are constructed, the DEA and SPF models used here estimate capacity by scaling up observed output to reflect each vessel's potential efficiency and capacity utilization increases (based on the observed, best practice technology).

Because separate measures of TE and CU are generated in the models, the measures will also be used to make comparisons between particular groups or time periods of interest. The specific comparisons include the pollock catcher-processor fleet as a whole before and after the AFA was implemented, between AFA-eligible and AFA-ineligible vessels, and among vessels within particular companies. These comparisons provide information on how average TE and CU changed post-AFA, whether decommissioned vessels had historically lower average TE and CU than continuing vessels, and whether such measures are good indicators of companies' likelihood to idle AFA-eligible vessels, respectively. The predictive power of the TE and CU measures in idling and decommissioning decisions is also more formally assessed through Logit models.

The next section introduces and details the methodology underlying the SPF and DEA models. Those readers unfamiliar with, or not interested in, the technical aspects of the SPF and DEA models (and their use in capacity estimation) may consult the non-technical appendix for a purely intuitive description. The third section discusses the data used and the results obtained. The paper concludes with a further discussion of the findings and of the necessary caveats that must be kept in mind when interpreting the results.

II. Capacity Estimation in DEA and SPF Models

The theoretical basis of the DEA and SPF models is the distance function, which provides a complete characterization of multi-input, multi-output technologies. Distance functions are typically specified with an output or input orientation, where each provides slightly

[2] Both DEA and SPF have particular strengths and weakness, but a complete comparison of the models is beyond the scope of the current paper. For a discussion, see Coelli, Rao, and Battese (1998) or Holland and Lee (2001).

different information. The output distance function, $D_o(\mathbf{x,y})$, provides information regarding the potential increases in output from a given set of inputs (relative to the estimated production possibilities frontiers [PPF]), while the input distance function, $D_i(\mathbf{x,y})$, indicates the amount by which input use could be decreased to achieve a given level of output (relative to the estimated input isoquants). The current application focuses on an output orientation, since a main area of interest is estimating how potential catch (output) for the catcher-processor fleet has changed after the AFA buybacks.

As discussed by Färe and Primont (1995), the output distance function is defined on the producible output set, $Y(\mathbf{x})$, as $D_o(\mathbf{x,y}) = \min_\beta \{\beta: (\mathbf{y}/\beta) \in Y(\mathbf{x})\}$. Thus, $D_o(\mathbf{x,y})$ gives the largest radial expansion of the output vector for a given input vector that is consistent with the output vector belonging to $Y(\mathbf{x})$, where it is assumed that potential increases in output preserve the observed output mix[3]. It can easily be shown that $D_o(\mathbf{x,y}) \leq 1$ for all feasible output bundles, where $D_o(\mathbf{x,y})=1$ along the frontier, and deviations below one indicate increasing levels of technical inefficiency. As a result, the value of the output distance function at each observation gives a measure of TE.

Although DEA and SPF both attempt to identify a best-practice frontier for a group of producers, they differ fundamentally in the way they generate the frontiers. DEA is a non-parametric method that uses mathematical programming to construct a piece-wise linear representation of the frontier of a technology. Deviations from the frontier are measured and used to construct efficiency scores, which can be interpreted as the estimated values of an output distance function. Alternatively, SPF is an econometric approach that estimates parameters for a functional representation of a technology, and disentangles deviations from the estimated frontier into random error and inefficiency. TE (distance function) estimates scores are then computed from the estimated parameter values and residuals.

Because SPF and DEA models were originally developed for estimating TE, one must make some adaptations in order to use them to generate estimates of *capacity* (which requires not only estimating the production possibilities frontier, as in the TE models, but also estimating how far out it can shift). The change one makes to each of the standard DEA and SPF models

[3] One possibly restrictive aspect of this assumption is that actual increases in output may not hold the current output mix constant. Changes in relative prices, stock conditions, or regulations (for both target or bycatch species) may dictate a different output mix. Directional distance functions can be employed in order to find increases in output

depends upon one's interpretation of what is represented by "capacity." The different definitions of *technical*[4] capacity that have been suggested in the literature all correspond to some maximum quantity of output, but differ in their assumptions regarding the level of variable inputs used in conjunction with the capital stock. The approach taken here is to base the measure of technical capacity on a maximal level of variable input use following Johansen (1968), Färe, Grosskopf, and Kokkelenberg (1989), and Kirkley and Squires (1999).

More specifically, the definition offered by Johansen[5] is " the maximum amount that can be produced per unit of time with existing plant and equipment, provided the availability of variable factors of production is not restricted." This definition of capacity corresponds to the output that could be produced under technically efficient production with variable inputs fully employed, but constrained by the fixed factors and the state of technology. However, when the Johansen notion is employed in an empirical setting, and in particular, one where catch is governed by a TAC, the variable input use may be far less than theoretically "unrestricted" levels. This implies that resulting capacity estimates are likely to be more realistically obtainable than the strict definition connotes -- essentially representing the most output obtainable from a set of fixed factors and the maximum observed variable input use.

It is fairly straightforward to adapt each of the standard DEA and SPF models to generate such estimates of capacity. The DEA model of Färe, Grosskopf, and Kokkelenberg (1989, hereafter referred to as "FGK"), to be discussed further later, was constructed so as to directly correspond to Johansen's definition. As a result, it is easier to implement than SPF when one is seeking a Johansen-based measure of capacity. The "unrestricted" variable input levels in the DEA model are determined internally in the model by first selecting groups of "peers" with similar fixed inputs, and then finding the maximum observed variable input levels for each group. The SPF approach is slightly more complicated, as one must manually specify the unrestricted variable input levels associated with groups sharing similar fixed input endowments. Possible specifications include the maximum *theoretical* variable input levels (such as operating

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for *any* type of expansion -- not just radial -- but given the biological/technical interdependencies and limited species caught by this fleet, the observed mix seems to be a reasonable expansion path.

[4] This paper focuses on technical capacity rather than "economic" capacity, which has traditionally been defined in terms of the output corresponding to a tangency between a short-run average cost curve and a long-run average cost curve. The technical focus here is due to the current lack of cost data.

[5] Johansen's definition is equivalent to the current FAO definition of capacity agreed upon by researchers representing several nations at a Technical Working Group meeting. It is also equivalent to that offered by Christy (1996), Prochaska (1978), and the Federal Fisheries Investment Task Force Report to Congress.

24 hours a day, 365 days a year), the maximum *observed* levels of each individual vessel, or the maximum *observed* variable input levels of *all vessels* with similar fixed input endowment. The approach taken here is to use the last specification, which is essentially what is done in the DEA program. Thus, catcher-processors will be grouped according to their size (less than 230 feet in length or greater than or equal to 230 feet in length[6]) and the maximum variable input use[7] for each group will be used as to represent their unrestricted levels. Note that this choice also makes the SPF and DEA models more similar and comparable, thus increasing the ability to examine the robustness of estimates under alternative stochastic and non-stochastic specifications.

DEA Specifications

Turning the focus to the DEA specification, as described in Färe, Grosskopf, and Lovell (1985, 1994) and Coelli, Rao, and Battese (1998), the following output-oriented DEA linear program computes the technically efficient output:

$$Max_{(\theta,z)}\ \theta \tag{1}$$

subject to the following restrictions:

$$\theta\, y_{jm} \le \sum_{j=1}^{J} z_j\, y_{jm},\ m = 1,2,\ldots M$$

$$\sum_{j=1}^{J} z_j x_{jn} \le x_{jn}\ , \quad n = 1,2,\ldots N$$

with $z_j \ge 0$, $j = 1,2,\ldots,J$

$$\sum_{j=1}^{J} z_j = 1$$

The "activity levels" (z_j) of y and x are the weights for the points on the linear segments that define the frontier. The first three constraints ensure that the observed output bundles stay on or within the feasible set, while the last constraint allows for variable returns to scale (VRS). A VRS approach is used here to ensure that each vessel is only benchmarked against vessels of similar size, as projected points for vessels below the frontier are formed as a convex (rather than linear) combination of frontier observations (Coelli, Rao, and Battese, 1998).

[6] The 230-foot vessel length was not chosen arbitrarily or in accordance to some federal or ADF&G size classification. Rather, the data elicited a distinct natural break between size classes at 230 feet.
[7] In this paper, the variable inputs are given by crew size, days at sea and tow duration, and fixed inputs are given by

The value of the parameter θ is the reciprocal of the output distance function, $D_o(\mathbf{x},\mathbf{y})$, and therefore provides a measure of the possible (radial) increase in outputs under full TE. Using the results from the program above, which is solved for each vessel in the data, one can determine the technically efficient output for each vessel by scaling observed output levels by θ. For example, an objective value of θ =1.1 indicates that a vessel's technically efficient output equals 1.1 times its current observed output vector.

Although DEA models were originally designed to measure TE, FGK proposed a variation of the standard DEA model given above that was explicitly designed to provide measures of capacity output and utilization corresponding to Johansen's "unrestricted" definition of capacity discussed earlier. To implement the FGK DEA model, one computes the maximum proportionate increase in outputs, ϕ, when variable inputs are allowed to vary, but fixed inputs are held at observed values. The following output-oriented linear program also allows for VRS:

$$Max_{\ (\phi, z, \lambda)}\ \phi \qquad (2)$$

subject to the following restrictions:

$$\phi\ y_{jm} \leq \sum_{j=1}^{J} z_j\ y_{jm},\ m = 1,2,...M$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}\ , \quad for \quad n \in \alpha\ ;$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq \lambda_{jn}\ x_{jn}\ , \quad for \quad n \in \hat{\alpha}\ ;$$

with $z_j \geq 0$, $j = 1,2,...,J$

$$\lambda_j \geq 0\ , \quad for \quad n \in \hat{\alpha},$$

and $\sum_{j=1}^{J} z_j = 1$

The variable factors are denoted by $\hat{\alpha}$, the fixed factors are denoted by α . Because each vessel's use of variable inputs is not restricted to their observed levels in the FGK model, the third constraint involving λ is incorporated, telling one the necessary variable input use required to achieve frontier output levels. Note also that to be on the frontier in the FGK model, vessels must have produced the most output for a given level of *fixed* inputs. Firms that are not on the

vessel length, tonnage, and horsepower.

frontier may be below it because they are either using fixed inputs inefficiently, or because they are using lower levels of variable inputs than frontier vessels (or both).

Using the results from the program above, one obtains vessel-level capacity estimates by scaling each vessel's observed output vector by its estimated value of ϕ – here termed a capacity score, similar to θ in the standard TE model. Estimates of capacity for the fleet or fishery as a whole are obtained by summing the capacity estimates of all individual vessels[8]. In addition, CU scores for each vessel may be constructed through the ratio of θ / ϕ . This ratio provides a measure of CU that reflects the potential increase in output solely from increased variable input use, and not from increased technical inefficiency[9]. The interested reader should see FGK (1989) for further details.

SPF Specification

The SPF approach uses a parametric model to econometrically fit the frontier of technologies while simultaneously disentangling observed deviations from the frontier into two parts: random variation or noise and productive inefficiency. The functional representation of production technologies in SPF models has typically been limited to single output production functions, but will be expanded here to accommodate the multiple output technology through use of a ray production function.

The familiar single output SPF model (see Kumbhakar and Lovell, 2000) typically expresses production technologies in terms of

$$y_{it} = f(\mathbf{x}_{it};\boldsymbol{\beta})\cdot\exp\{e_{it}\} ; \qquad (3)$$

$$e_{it} = - u_{it} + v_{it},$$

where y is the output, f(•) is a functional representation of the production technology, **x** is a vector of inputs, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and *e* is a random error term. Note that actual output, y, may differ from potential output due the observed error, *e,* which is usually specified as including two components.

[8] In the presence of increased stock or congestion externalities, fleet capacity may be *less* than the sum of individual vessel capacities.

[9] Primal CU measures have typically been constructed as $CU=Y^{observed}/Y^{capacity}$. However, if $Y^{observed}$ is lower than $Y^{capacity}$ primarily because of technical inefficiency, then the CU measure's interpretation becomes confounded. By constructing $CU=Y^{technically\ efficient}/Y^{capacity} = \theta / \phi$, as done here and developed in FGK, the interpretation of CU measures is clearer, and reflects only increases in output from increased variable input use – not increased technical efficiency.

The first component represents differences between observed and potential output due to inefficient input use, and is denoted by u. The second component, v, is attributed to purely random variations in output (unrelated to inefficient factor use), analogous to the error term in standard regression models. In fisheries contexts, such random errors are often attributed to weather conditions, variations in stock conditions, luck, or possibly introduced by measurement error.

In this paper it is assumed that v is an independent and identically distributed (i.i.d.) N(0, σ_v^2) random variable, and u is distributed as a truncation at zero of the N(m_{it}, σ_u^2) distribution, where $m_{it} = \Sigma_i D_{it} \cdot \delta_i$, and D_{it} is a dummy variable equal to one for the i^{th} vessel in each period, zero otherwise. This approach makes use of the panel nature of the current data set, allowing for TE estimates that reflect potentially different efficiency levels and patterns and for each vessel. See Kumbhakar (pg. 83) and Coelli, Rao, and Battese (pg. 235) for further discussions on this specification.

An additional parameter, γ, is introduced here in order to ease the maximum likelihood estimation (MLE) of the variance parameters. First, a "combined" variance is constructed in terms of the random error and inefficiency term, given by $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$. Next, the parameter γ is defined as $\gamma = \sigma_u^2 / \sigma_s^2$. This reparameterization allows one to undertake a grid search for γ, which by definition must lie between 0 and 1, which is much easier than attempting to estimate σ_v^2 and σ_u^2 individually (which may lead to negative variances in some cases).

Two alternative functional representations that allow for multiple-output primal specifications are the distance function and the ray production function (to be defined shortly). They also allow for the two-part error decomposition discussed in the previous single output model. While these two functions differ in the way they are implemented, either can be used to estimate technically efficient output and to construct estimates of capacity. However, difficulties often arise when using the stochastic output distance function in applications in which there are zero-valued outputs[10].

[10] The problems arise because a lack of data on the dependent variable ($D_o(\mathbf{x},\mathbf{y})$) prohibits one from directly estimating the model. The approach typically used to overcome this problem is to recognize the linear output homogeneity of the distance function, which generates the equality $D_o(\mathbf{x},\lambda\mathbf{y}) = \lambda\, D_o(\mathbf{x},\mathbf{y})$. Next, λ is specified as the inverse of either one of the outputs, y_i^{-1}, or the Euclidean norm of the output vector, $\|\mathbf{y}\|^{-1}$, and logs are taken. The result is an equality that now has an observable left-hand-side variable for estimation: $-\ln\|\mathbf{y}\| = \ln D_o(\mathbf{x},\mathbf{y}/\|\mathbf{y}\|) - \ln D_o(\mathbf{x},\mathbf{y})$. However, for any observation in which y_i is equal to zero, the logarithm of the right-hand side variable is undefined, precluding estimation of the model.

Such problems are avoided here by utilizing a different but equivalent representation of the technology that is not subject to problems with zero-valued outputs: the stochastic ray production function (Löthgren, 1997). The ray production function model is derived by augmenting the standard, single output production given by

$$f(\mathbf{x}, \boldsymbol{\Omega}) = \max \{y \in R_+ : y \in Y(\mathbf{x}, \boldsymbol{\Omega}) \}, \tag{4}$$

where $\mathbf{x} \in R^N_+$, $Y(\mathbf{x}, \boldsymbol{\Omega})$ is the producible output set, and Ω includes all regulatory variables and stock information in each period (e.g., abundance, fish size and age distribution, and fish spatial and temporal distribution). Information on Ω in the current application is limited to annual Bering Sea stock estimates for each of the fleets' primary catch (pollock, flatfish, Pacific cod), since for the most part, regulatory effects are difficult to quantify and thus will be viewed as a latent variable that impacts the shape and location of $Y(\mathbf{x},\boldsymbol{\Omega})$, following Weninger (2001). This single-output representation is transformed into a multiple-output generalization of the production function by expressing the output vector of a multi-output technology in polar-coordinate form:

$$\mathbf{y} = \|\mathbf{y}\| \cdot m(\theta), \tag{5}$$

This form for y implies that the multiple-output ray production function takes the form:

$$f(\mathbf{x},\theta, \boldsymbol{\Omega}) = \max \{\|\mathbf{y}\| \in R_+ : \|\mathbf{y}\| \cdot m(\theta)) \in Y(\mathbf{x}, \boldsymbol{\Omega})\}. \tag{6}$$

Here, $\mathbf{y} \in R^M_+$, $\|\mathbf{y}\|$ is the Euclidean norm of the output vector ($\|\mathbf{y}\| = (\sum_{i=1}^{m} y_i^2)^{1/2}$), θ represents the polar-coordinate angles of the output vector (rather than the standard rectangular coordinates), and the function m: $[0, \pi/2]^{M-1} \rightarrow [0,1]^M$ is defined in terms of the output polar-coordinate angles as

$$m_i(\theta) = \cos\theta_i \prod_{j=0}^{i-1} \sin\theta_j,\ i=1,\ldots M, \tag{7}$$

where $\sin\theta_0 = \cos\theta_M = 1$. The vector of polar-coordinate angles θ (which are used in estimation) are easily obtained from the inverse transformation of (7), $m^{-1}(\mathbf{y} / \|\mathbf{y}\|)$, or

$$\theta_i(\mathbf{y}) = \cos^{-1}(y_i / \|\mathbf{y}\| \prod_{j=0}^{i-1} \sin\theta_j),\ i=1\ldots M\text{-}1 \tag{8}$$

While the conventional single-output production function given in (4) represents the maximum output obtainable from a given bundle of inputs, the multiple output ray production function in (6) represents the maximum (frontier) output *norm* obtainable given inputs and the observed output mix (as represented by the output polar coordinates[11]). In addition, if $Y(\mathbf{x}, \boldsymbol{\Omega})$ satisfies standard assumptions[12], the ray function is positively monotonic in inputs, or $f(\mathbf{x}'', \theta, \boldsymbol{\Omega}) \geq f(\mathbf{x}', \theta, \boldsymbol{\Omega})$, $\forall\ \mathbf{x}'' \geq \mathbf{x}'$.

To model the technology in the context of the SPF framework discussed earlier, the link between the ray production function and the output distance function can be exploited to allow for a natural decomposition of inefficiency and random error. This relationship is easily derived by recognizing that, by definition, the output distance function represents the ratio of the observed output norm to the frontier output norm (Shephard, 1970). Thus, in the context of the ray production frontier this relationship implies

$$D_o(\mathbf{x},\mathbf{y}) = ||\mathbf{y}|| \,/\, f(\mathbf{x}, \theta, \boldsymbol{\Omega}), \tag{9}$$

which can be rearranged to yield

$$||\mathbf{y}|| = f(\mathbf{x}, \theta, \boldsymbol{\Omega})\cdot D_o(\mathbf{x},\mathbf{y}). \tag{10}$$

One may then specify (10) as in the standard SPF framework in (3) by including a symmetric multiplicative random error term, $\exp(v)$, and representing the output distance function as $D_o(\mathbf{x},\mathbf{y}) = \exp(-u)$ (which as required by theory, is bounded between zero and one):

$$||\mathbf{y}|| = f(\mathbf{x}, \theta, \boldsymbol{\Omega})\cdot\exp\{-u + \mathrm{v}\} \tag{11}$$

Estimation can then proceed just as with the single-output framework once a suitable flexible functional form is chosen for $f(\mathbf{x}, \theta, \boldsymbol{\Omega})$. The form chosen here was the translog[13]:

$$\ln ||\mathbf{y}_t|| = \beta_0 + \sum_{j=1}^{(m+n)} \beta_j\cdot\ln(z_{jt}) + \sum_{j\leq k}\ \sum_{k=1}^{(m+n)} \beta_{jk}\cdot\ln(z_{jt})\cdot\ln(z_{kt}) - u_{it} + v_{it},$$

where the vector $\mathbf{z}$ includes each of the $m-1$ polar coordinate angles (θ's), the n fixed and variable inputs, m annual species stock indices (each species-specific stock estimate was normalized relative to 1994), and a time variable (t) to capture/represent potential technological change. As mentioned earlier, the inefficiency component of residuals, u_{it}, was parameterized as

[11] The polar coordinate angles (θ) represent the curvature of the production frontier, which may be derived from the partial derivatives of the ray function with respect to the polar-coordinate angles, $\partial f(\mathbf{x}, \theta)/\partial\theta_i$, $i=1,\ldots M-1$.

[12] Specifically, if inputs are strongly disposable (meaning that if a given input bundle can produce a certain level of output, then a larger bundle of inputs can also produce that output), then input monotonicity holds.

[13] Note that even though a logarithmic form is used to approximate (11), there are no problems in the case of zero-valued outputs, as $\log(\theta_i \mid y_i=0)$ is well defined (see (8)).

$u_{it} = \Sigma_i D_{it} \cdot \delta_i$, where D_{it} is a dummy variable equal to one for the i^{th} vessel in each period, zero otherwise[14].

Vessel-level TE scores (estimates of $D_o(\mathbf{x,y})$), can be computed as $TE_{it} = E[\exp(-u_{it}) | e_{it}]$. Kumbhakar and Lovell (2000) provide further details on the specific formula used in the conditional expectation and the likelihood function for the MLE procedure.

Once the ray frontier model has been estimated, capacity estimates are obtained by evaluating the efficient frontier at the maximal levels of variable inputs discussed earlier. And, with individual vessel capacity estimates in hand, estimates for the fleet as a whole are computed by summing capacity output for each vessel in the fleet for each species caught. These computations result in an estimate of the fishing capacity for each different species in the fishery. In addition, just as with the DEA models, CU measures will be constructed as the ratio of technically efficient output to capacity output, where in this case $Y^{\text{technically efficient}} = Y^{\text{observed}} / D_o(x,y)$, and $Y^{\text{capacity}} = Y^{\text{technically efficient}}|_{\text{x maximum}}$.

III. Data, Model Results and Discussion

Both the SPF and DEA models were estimated according to the techniques discussed in the previous sections using 180 observations representing annual catch for 30 vessels over 1994-2000 (some vessels did not participate in all years). Within the models, "outputs" were given by total annual catch of pollock, flatfish, and Pacific cod[15], "variable inputs" were specified by total annual days at sea, annual tow duration (in hours) and annual crew (in man-weeks), "fixed inputs" were given by vessel length, tonnage, and horsepower, and "non-discretionary inputs" given by annual stock estimates for pollock, flatfish, and Pacific cod. Data for these variables was obtained from the NMFS "blend" catch estimates, the federal observer program, weekly processing reports, federal and ADF&G vessel registration files, U.S. Coast Guard data, and the 2000 NMFS stock assessment and fishery evaluation report.

Estimating the SPF model first entailed testing several forms of the translog specification with generalized likelihood ratio tests[16]. The test results indicated that the null hypothesis of a

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[14] One of the vessel dummies was excluded to avoid the "dummy variable trap", so there are 29 dummy parameter estimates and a standard intercept for the inefficiency parameterization.

[15] These three species groups were incorporated because each comprised greater than 5% of total catch in each year. Any species not meeting this minimum requirement was not included in the model.

[16] The restricted forms that were tested were a purely linear relationship, a form with only linear and cross terms, a form with only linear and squared terms included, and a combination of latter two restricted forms.

restricted version of the full translog specification could not be rejected as an appropriate representation of the ray frontier function. This restricted specification included the linear and squared terms of the variables discussed above, but omitted some of the cross-terms involving vessel tonnage, tow duration, days at sea, and stock indices[17]. The parameter estimates, standard errors, and asymptotic t-ratios associated with the final specification are given in Table 1. Annual mean values for data used in the analysis for 1994-2000 are given in Table 2.

As discussed earlier, the capacity estimates developed within the SPF and DEA models reflect potential increases in output due to increased TE and CU. For this reason, a discussion of the TE and CU measures underlying the capacity estimates will be provided first. Note that the values of corresponding DEA and SPF measures do differ slightly for each vessel, as would be expected when employing different empirical techniques, but the relative values of the DEA and SPF measures for each vessel are quite similar. The Spearman rank correlation coefficient[18] between DEA and SPF TE scores is 0.84, and the coefficient between the corresponding CU scores is 0.92. Note also that the patterns exhibited among the groups and time periods to be compared are essentially always the same for the two approaches -- a somewhat comforting result. Therefore, the following discussion will reference the overall trends in TE and CU without explicitly recognizing minor differences in the values of the SPF and DEA estimates.

The results in Table 2 illustrate the annual changes that occurred in a variety of areas. Technical harvesting efficiency generally increased over the sample period, and markedly so after implementation of the AFA in 1999. The same can be said for CU, which had its lowest value in 1994 and peaked in 2000. There was also an increase in the percentage of boats with meal plants onboard, a result likely due to the increased retention and utilization requirements of 1998. The presence of a meal plant onboard seems to also be correlated with decisions over vessel buyouts in 1999, and the choices to idle AFA-eligible vessels in 1999 and 2000.

The average per-vessel catch of pollock increased by 20% in 1999, and rose again in 2000 by an additional 25% (though the *total* apportionment of catch to these vessels actually fell by 42% in 1999 and then increased only 16% in 2000). These per-vessel increases can be

[17] In initial runs, the cross terms involving these variables were insignificant and in some cases resulted in output elasticities of incorrect sign (violating curvature conditions). Once the insignificant cross terms were omitted from the model (after generalized likelihood ratio tests verified their lack of significance) all expected monotonicity conditions were met.

attributed to the exit of nine vessels in 1998, the idling of AFA-eligible vessels within multi-vessel companies, and the sale of quota from one AFA-eligible vessel to the PCC. The average days at sea also increased from past levels in 1999, and reached an historical peak of 140 days in 2000. The per-vessel averages for towing duration and annual crew use exhibited a similar trend. These changes in season length and annual effort are likely results of decreases in the number of participants and an absence of the former race for fish.

Table 3 provides the capacity estimates that result from scaling up observed catch to reflect potential increases from heightened TE and CU. Focusing on pollock, the average of DEA and SPF technical capacity estimates reached a peak of nearly 1.1 million tons in 1994, dropping to around 880,000 tons in 1998. In 1999, post-AFA, pollock capacity dropped by around 300,000 tons, nearly a 35% decline (rising slightly from this level in 2000). At the same time, total catch (and capacity) for Pacific cod and flatfish was cut in half from previous historical levels and fell again in 2000 (though much more significantly for Pacific cod than flatfish).

Table 3 also shows how the total "effort" (days, duration, crew) and "capital stock" (tons, length, horsepower) used in harvesting and processing have changed since the AFA was implemented. The numbers shown for effort are summed over all vessels for all weeks in the year. Generally, the total fishery effort variables fell by around 30% in 1999, and rose slightly in 2000. Total capital stock variables for the fleet reflect the sum of each of the vessel characteristics over all vessels that participated in the fishery in each year. While these representations of capital are admittedly crude and ignore processing equipment onboard, they do provide a rough indication of the aggregate "fishing power" and likely provide more information than merely stating the number of vessels that participated[19]. These measures of capital peaked in 1994 and were at their lowest in 2000. As with some of the previously discussed measures, this decline is mainly attributable to the AFA buyback and the idling of vessels in 1999 and 2000.

It should be evident at this point that some marked changes occurred in this fleet after the AFA was implemented. However, it is not entirely clear at first glance whether the increases in

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[18] The Spearman rank correlation coefficient is defined as $S = 1 - [6*\Sigma_i(R_i - Q_i) / n(n^2 - 1)]$, where R_i is the rank of vessel *i* in the SPF rankings (ranked according to either TE or CU scores), Q_i is the rank of vessel *i* in the DEA rankings, and n is the number of observations.
[19] In addition, it is fairly common to use measures of vessel length, tonnage, and horsepower as proxies for capital.

TE and CU occurred because the decommissioned vessels were historically lower in these areas than continuing vessels, or if the continuing vessels' TE and CU rates sharply increased because of the provisions in AFA. Therefore, it is instructive to analyze the historical relative performance of the AFA-eligible and AFA-ineligible vessels from 1994-1998 to see how they fared relative to one another. In addition, the TE and CU of the AFA-eligible, non-idled vessels will be analyzed from 1994-2000 to see if their performance changed after 1998 relative to the past. Each of these questions will now be addressed in turn.

Table 4 provides a comparison of the average values of different measures for each of the AFA-eligible and AFA-ineligible groups. While the CU levels for eligible vessels are only slightly higher than ineligible vessels, the differences in TE are much larger, by about 0.119 on average. This implies that comparably sized eligible vessels produced on average about 16% more output than the ineligible vessels for a given level of effort for 1994-1998[20]. However, the eligible vessels were on average much larger and more powerful than the ineligible vessel (and thus had greater mean catch levels for pollock). One potential cause of the greater TE exhibited by the (larger) eligible vessels could be scale efficiencies; elasticity of scale estimates from the SPF model, computed as the sum of output elasticities ($\Sigma_i\ \partial \ln\|\mathbf{y}\| / \partial \ln x_i$), indicate the presence of increasing returns to scale.

The additional question of whether the non-idled eligible vessels exhibited increased TE and CU after implementation of the AFA can be addressed by examining Table 5. For this subset of vessels, the TE estimates from the DEA and SPF models differ more in magnitude than the previous comparisons, but still show the same annual patterns[21]: the lowest scores occur in 1994, and the highest scores in 1997 (and 2000 for the SPF model).

There are at least two potential explanations for why the TE scores in 1997 exceed those after the AFA was implemented. First, after 1997, increased retention and utilization requirements dictated that meal production became an integral part of processing. While decreasing discards overall, this activity slows the harvesting-processing chain down more than

[20] For example, the average of DEA and SPF TE scores for eligible vessels is .8585, and the average for ineligible vessels is 0.743. Thus, for a given vessel size and effort level, $Y^{eligible}/0.8585=Y^*$, and $Y^{ineligible}/0.743=Y^*$, or $Y^{eligible}=1.16 \cdot Y^{ineligible}$.

[21] The DEA scores show a greater amount of variation from year to year relative to the SPF scores. The lowest SPF score (in 1994) only differs from the highest (in 1997 and 2000) by 0.028, while the lowest DEA score (in 1994) is 0.107 less than the highest (in 1997). This result is to be expected, as DEA is more sensitive to year-to-year changes while SPF models tend to smooth out such shocks to some degree. See Coelli, Rao, and Battese (pg. 240) for a further discussion of this issue.

simply discarding undesirable catch. Such effects compounded with increasing Stellar sea lion closures could have offset some of the potential gains in harvesting efficiency afforded by the post-AFA changes. Second, it is possible that the potential gains in harvesting efficiency were small; most of the perceived gains of the AFA seem to be related to processing, and the associated increases in product recovery rates[22] and product grades. In fact, it is likely that tradeoffs were made between harvesting efficiency and the quality of processed products, as evidenced by the observed slowdown of operations. However, since the present analysis does not account for differences in processing and quality, only the effects on harvesting efficiency are evident.

An additional question to be examined is how the AFA-eligible vessels that were idled in 1999 or 2000 differed from the active, eligible vessels. In particular, one might wonder if the TE and CU scores constructed here could be used as an indicator of which vessels were likely to be idled within a company (in situations where a company owned multiple vessels). To examine this question, Table 6 presents a variety of average measures for the two groups of vessels (AFA eligible/idled and AFA eligible/active) over the periods prior to implementation of the AFA.

With regard to technical harvesting efficiency, the active vessels' average TE scores exceeded idled vessels' corresponding scores by about 0.1 on average from 1994-1998, producing approximately 13% more than idled vessels for a given vessel size and effort level. The CU scores of active vessels greatly exceeded those of the idled vessels for the 1994-1998 period, by an average of around 0.16 for the SPF and DEA models. These findings together suggest that the vessels that were active post-AFA had historically caught more fish for a given vessel size and effort level than did vessels that were idled post-AFA, and that the active vessels exerted considerably more fishing effort than similarly sized idled vessels for the 1994-1998 period. While the available data does not provide detailed information *why* the AFA-active vessels had been utilized to a greater degree prior to the AFA, information regarding the existence of a meal plant onboard does provide an additional possible reason certain vessels were idled. Only 20% of the AFA-idled vessels had meal plants on board, while 70% of the AFA-active vessels had the capability to produce.

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[22] The product recovery rates are reported to have increased by 26% during 1999 over the 1998 baseline, and by 35% in 2000 relative to 1998 (PCC and HSCC, 2001).

To more formally evaluate the predictive power of the CU and TE scores in idling or eligibility decisions, logit models were run. The premise of these regressions was that the observed choices could be explained by TE and CU scores. A dummy variable for the ability to produce meal was also included in the models[23], as this factor may have been important in such decisions and was not included in the original frontier models. Table 7 shows the result of four logit models for the following four choices: 1) AFA-eligible vs. AFA-ineligible; 2) eligible-active vs. eligible-idled; 3) eligible-active vs. eligible-idled for just company 1; and 4) eligible-active vs. eligible-idled for just company 2[24].

The results of the models indicate that the predictive power of the TE and CU scores (and meal producing ability) is pretty good. These factors led to correct predictions 78 percent of the time for eligible vs. ineligible status, with TE scores and meal capability contributing significantly (CU scores were highly insignificant). For the active or idled status of AFA-eligible vessels, the logit model had 85 percent of the predictions correct, and was significantly influenced by CU and meal capability.

A similar level of predictive power emerged when models were run comparing an individual company's idled/active vessels, yielding correct predictions for 83 percent of the observations for company 1, and 74 percent correct for company 2. Within the company 1, two vessels were idled. One of these vessels exhibited the lowest TE score for all vessels in that company for 1994-1998 according to both the DEA and SPF models. It is also lacking a meal plant, is relatively small, and exhibited less than average CU relative to the other vessels in the company. The other idled vessel, however, is not quite as obvious a candidate for idling. For example, it *does* have meal capability and ranks among the highest in TE scores according to the SPF model (and near the middle for DEA). Instead, it is the CU scores that point to this vessel as a potentially less desirable vessel to operate; both SPF and DEA scores indicate that this vessel has by far the lowest historical utilization rate of all vessels in the company. This result could be due to the age, lack amenities on board, processing inflexibility, or a host of other factors. Still, one might think that a vessel that was utilized relatively little in the past may not be as useful to a company looking to diminish their active fleet size.

[23] The meal dummy was not be included in the company specific idled/active regressions, as vessel's status was perfectly predicted by the presence of a meal plant when included in the model, prohibiting convergence.
[24] There were only two companies who had multiple vessels and chose to idle one or more of them. For confidentiality reasons we will refer to them as company one and company two.

Turning to the company 2, one finds that 3 vessels were idled in 1999 or 2000. According to both the SPF and DEA models, these 3 vessels exhibited the lowest TE scores in the company (two of which are especially low). Exacerbating this potential shortcoming is a lack of meal plants onboard for any of these 3 vessels and the presence of meal capability for all other active vessels. The CU scores for these vessels seem a bit less consistently informative with regard to the idling decision than with the former company, as the CU scores are near the lowest for two of the three vessels, but relatively high for the other. This result is also supported in the logit model for company 2, in which the coefficient on CU was highly insignificant.

It should be noted that the discussion of the relative CU and TE scores up to this point has made little mention of whether two groups were "significantly" different. While remarks have been made regarding differences in magnitude of measures for two groups or time periods, no formal statistical tests have been conducted on whether the differences are significant relative to the overall variation in the estimates. In order to examine these issues more formally, and to solidify the findings of the previous discussion, hypothesis tests were carried out regarding the equality of TE and CU scores for several comparisons of interest. In particular, tests for equality of means (for TE and CU) were carried out for the following groups: AFA-eligible and AFA ineligible vessels, AFA-eligible/active vessels before and after the AFA was implemented, AFA-eligible/active and AFA-eligible/idled vessels, vessels with and without meal plants, and inter-company comparisons.

To carry out these tests, the two-step method (Ray [1991], Fizel and Nunnikhoven [1992], and McCarty and Yaisawarng [1993], Yu [1998]) was employed[25]. This approach involves regressing the TE (and CU) scores from a first-stage model upon continuous or categorical uncontrollable variables in order to find explainable differences among individuals or groups with different characteristics (that are not explicit inputs in the production process). Here, the TE and CU scores for two groups or periods were regressed upon dummy variables for each of the groups or periods, facilitating inference through statistical tests of whether the mean

[25] The two-stage approach was applied only to the DEA results only because of the distributional assumptions that are present in the SPF model. In particular, in the first stage it is assumed that the inefficiency effects are independently and identically distributed. The second stage regression looks for firm or group specific factors that explain the inefficiency effects, implying that the effects are *not* identically distributed. One method for carrying out statistical tests on SPF results is the Wilcoxian signed-rank test (Sheskin, 2000), or the procedure outlined in Bera and Sharma (1999).

levels of TE or CU are different[26]. Because the TE and CU scores are truncated from below at one, a Tobit model was used to conduct the regressions. Next, hypothesis tests for equality of means (intercepts) between groups or periods of interest for the TE and CU scores were conducted.

The results of the tests are given in Table 8, and indicate the following: 1) the historical TE of AFA-eligible vessels exceeded that of AFA-ineligible vessels; 2) the CU of AFA-eligible vessels increased post-AFA relative to past years; 3) the pre-AFA TE and CU of AFA-eligible/active vessels exceeded that of the AFA-eligible/idle vessels; 4) the TE of vessels with meal plants was greater than that of vessels without meal plants; 5) the TE and CU scores of company 1's idled vessels were significantly lower than the active vessels; and 6) the TE scores of idled vessels within company 2 were significantly lower than their active vessels. The motivations for, and potential repercussions from, these differences were provided in the earlier discussion.

While TE and CU levels provide only a small part of the information necessary to assess overall vessel performance, as illustrated above they can be useful in assessing capacity and certain aspects of economic performance. In addition, owner's decisions to idle or operate a vessel – made by those best informed with regard to the relative profitability of vessels – appear to be considerably correlated with the TE and CU measures, which can be estimated using commonly available data in Alaskan FMP fisheries. However, as the meal capability factor illustrated above, there are other "real world" factors that must be considered along with these more abstract measures when analyzing the actions taken by vessel owners.

IV. Conclusion

In addition to the caveats placed on the extent to which these technological measures characterize profitability, it is important to note the potential biases and shortcomings of the existing measures. First, while efforts were made to incorporate as many of the inputs used in production for which data is available, the set included in the model is not complete. For example, vessel characteristic data is used as a proxy for heterogeneous capital or fixed inputs.

[26] Note that these tests look only at the distribution of the resulting DEA estimates when analyzing the significance of the differences in TE and CU among producers. Uncertainty regarding the first-stage estimates is not incorporated because of the non-stochastic nature of the DEA model.

However, it is unlikely that each of the vessels sharing the same length, tonnage, and horsepower have an identical, productive capital stock.

Similarly, the group of effort variables (days at sea, tow duration, crew size) representing "variable inputs" serve as proxies for the numerous inputs that are exhausted within a trip. The most obvious result of omitting relevant inputs is that the efficiency comparisons in the models may be affected. For example, if two vessels used identical levels of the observed inputs, but one vessel had much greater catch, the models would give it a higher TE score. However, it may be the case that this vessel used much more of another omitted input and is thus not more efficient than the other.

The second potential shortcoming of the current models relates to possible misinterpretation of the capacity estimates. As discussed in the introduction, these measures, while based on observed production, are physical/technical measures and do not necessarily represent what *would* be produced -- just what *could* be produced. And further, what could be produced if captains could somehow increase harvesting efficiency to match other similarly sized vessels, and could increase the amount of time spent fishing to match the highest levels exhibited by vessels similar in size to theirs.

It should also be emphasized that "full" capacity utilization (CU=1) may not represent cost-minimizing or profit-maximizing effort levels for any or all vessels, and may not be realistically sustainable. That said, since the CU measures do provide an indication of how much one is attempting to get out of a vessel of a given size, they are likely have the greatest relevance in fisheries where there is almost certainly excess capacity at the individual vessel level. In such cases, greater values of CU are more likely to be correlated with lower costs per unit of output.

Finally, it is important to emphasize that the relative levels of TE estimated in the models represent only a portion of the factors that determine the profitability of a vessel. The measures constructed here examine how close a vessel lies to a production possibilities frontier, but ignore where the observed output mix is relative to a point of tangency between output shadow values and the iso-revenue surface (which determines the point of *allocatively* efficient production). Alternatively stated, the model does not judge whether the observed output composition is optimal given market prices, or whether input use is optimal given input prices, but looks solely at the quantity of output one gets from a given bundle of inputs. However, since both the technical and allocative elements have important and distinct roles in performance evaluation, information regarding the technical aspects can be enlightening if the findings are qualified appropriately.

Table 1. SPF Ray Production Function Parameter Estimates

Parameter	*Coefficient*	*Standard Error*	*Asymp. T-Ratio*
β_0 ; intercept	-9.770	0.988	-9.888
β_1 ; $\ln(\theta_1)$	6.567	1.265	5.191
β_2 ; $\ln(\theta_2)$	2.371	1.041	2.278
β_3 ; ln(length)	0.663	1.820	0.364
β_4 ; ln(tonnage)	0.507	0.368	1.377
β_5 ; ln(hp)	3.920	0.783	5.008
β_6 ; ln(duration)	0.999	0.509	1.962
β_7 ; ln(crew)	-1.058	0.818	-1.293
β_8 ; ln(days)	0.338	0.159	2.121
β_9; ln(pollock index)	10.322	0.742	13.915
β_{10}; ln(P.cod index)	0.693	2.696	0.257
β_{11}; ln(flatfish index)	35.806	0.385	92.890
β_{12}; ln(t)	3.184	0.106	30.144
β_{13} ; $\ln(\theta_1 \cdot \theta_2)$	2.527	0.910	2.777
β_{14} ; $\ln(\theta_1 \cdot \text{length})$	1.370	0.689	1.989
β_{15} ; $\ln(\theta_1 \cdot \text{hp})$	-1.171	0.282	-4.149
β_{16} ; $\ln(\theta_1 \cdot \text{crew})$	-0.198	0.103	-1.914
β_{17} ; $\ln(\theta_1 \cdot t)$	-0.046	0.019	-2.422
β_{18} ; $\ln(\theta_2 \cdot \text{length})$	0.585	1.643	0.356
β_{19} ; $\ln(\theta_2 \cdot \text{hp})$	-0.826	0.566	-1.460
β_{20} ; $\ln(\theta_2 \cdot \text{crew})$	0.806	0.411	1.958
β_{21} ; $\ln(\theta_2 \cdot t)$	-0.194	0.086	-2.252
β_{22} ; ln(length·hp)	0.034	0.342	0.101
β_{23} ; ln(length·crew)	-0.381	0.209	-1.823
β_{24}; ln(hp·crew)	0.068	0.126	0.536
β_{25}; ln(crew·t)	-0.029	0.014	-2.071
β_{26}; ln(pollock index·P.cod index)	17.102	1.195	14.307
β_{27}; ln(pollock index·flat index)	8.458	1.258	6.721
β_{28}; ln(P.cod index·flat index)	42.218	1.457	28.975
β_{29}; $(\ln(\theta_1))^2$	1.988	0.176	11.313
β_{30}; $(\ln(\theta_2))^2$	-0.302	0.230	-1.317
β_{31}; $(\ln(\text{length}))^2$	0.026	0.885	0.029
β_{32}; $(\ln(\text{tonnage}))^2$	-0.087	0.067	-1.295
β_{33}; $(\ln(\text{hp}))^2$	-0.343	0.207	-1.656
β_{34}; $(\ln(\text{duration}))^2$	-0.187	0.098	-1.899
β_{35}; $(\ln(\text{crew}))^2$	0.242	0.154	1.575
β_{36}; $(\ln(\text{days}))^2$	-0.210	0.201	-1.045
β_{37}; $(\ln(\text{pollock index}))^2$	-7.832	1.322	-5.923

Table 1. Ray Production Function Parameter Estimates (cont.)

Parameter	*Coefficient*	*Standard Error*	*Asymp. T-Ratio*
β_{38}; $(\ln(\text{P.cod index}))^2$	-47.700	1.138	-41.911
β_{39}; $(\ln(\text{flat index}))^2$	100.798	1.031	97.727
β_{40}; $(\ln(t))^2$	-0.235	0.026	-8.920
σ^2	0.020	0.003	6.009
γ	0.739	0.051	14.537
δ_0	-0.338	0.194	-1.743
δ_1	0.854	0.238	3.591
δ_2	0.762	0.256	2.980
δ_3	0.967	0.219	4.411
δ_4	0.354	0.265	1.336
δ_5	0.776	0.224	3.468
δ_6	0.597	0.217	2.747
δ_7	0.546	0.220	2.488
δ_8	0.621	0.210	2.959
δ_9	0.276	0.280	0.986
δ_{10}	0.574	0.215	2.667
δ_{11}	0.494	0.211	2.339
δ_{12}	0.295	0.250	1.180
δ_{13}	0.472	0.223	2.115
δ_{14}	-0.179	1.081	-0.166
δ_{15}	-0.424	0.635	-0.667
δ_{16}	0.556	0.221	2.520
δ_{17}	0.130	0.444	0.292
δ_{18}	0.272	0.274	0.995
δ_{19}	-0.608	0.619	-0.983
δ_{20}	0.261	0.328	0.794
δ_{21}	0.775	0.206	3.754
δ_{22}	-0.653	0.461	-1.415
δ_{23}	0.526	0.226	2.328
δ_{24}	0.705	0.215	3.281
δ_{25}	0.321	0.259	1.240
δ_{26}	0.980	0.226	4.346
δ_{27}	0.677	0.203	3.334
δ_{28}	0.633	0.219	2.887
δ_{29}	0.710	0.202	3.513

Table 2. Yearly Averages for Vessels in the Pollock Catcher-Processor Fleet, 1994-2000

	1994	1995	1996	1997	1998	1999	2000
SPF $D_o(x,y)$ (Efficiency)	0.797	0.814	0.828	0.817	0.803	0.848	0.873
DEA $D_o(x,y)$ (Efficiency)	0.799	0.843	0.803	0.873	0.824	0.852	0.939
Avg. Potential % Output Increase	25.3%	20.7%	22.6%	18.3%	22.9%	17.6%	10.4%
SPF Capacity Utilization	0.739	0.791	0.829	0.775	0.806	0.870	0.934
DEA Capacity Utilization	0.728	0.772	0.857	0.833	0.878	0.862	0.935
Avg. Potential % Output Increase	36.3%	27.9%	18.6%	24.4%	18.8%	15.5%	7.0%
% of Vessels with Meal Plants	40%	40%	40%	40%	40%	60%	70%
Pollock Catch (tons)	21,573	20,944	20,500	20,089	20,636	24,314	30,244
Pacific Cod Catch	448	655	806	861	864	817	434
Flatfish Catch	1,180	1,215	1,647	1,459	942	912	913
Pollock Stock Index	1.000	1.093	0.912	0.760	0.800	1.152	1.122
P. Cod Stock Index	1.000	0.985	0.880	0.754	0.716	0.725	0.666
Flatfish Stock Index	1.000	0.877	0.872	1.049	0.781	0.909	0.759
Days at Sea (vessel-days)	120	114	119	98	109	119	140
Tow Duration (hours)	1,571	1,324	1,481	1,226	1,325	1,257	1,606
Crew (man-weeks)	1,734	1,710	1,910	1,630	1,756	2,046	2,346
Registered Tonnage	1,417	1,408	1,426	1,426	1,435	1,725	1,699
Length (feet)	258	258	259	259	260	283	284
Horsepower	4,989	4,893	4,927	5,028	5,070	5,719	5,745

Table 3. Yearly Totals for Pollock Catcher-Processor Fleet, 1994-2000

	1994	1995	1996	1997	1998	1999	2000
Pollock Catch (tons)	647,203	628,334	594,508	582,588	598,440	413,340	483,907
Pacific Cod Catch	13,432	19,659	23,376	24,973	25,044	13,897	6,937
Flatfish Catch	35,403	36,439	47,750	42,297	27,304	15,505	14,607
SPF Pollock Capacity	1,086,901	948,871	866,749	932,710	925,185	534,824	572,306
DEA Pollock Capacity	1,106,769	963,332	872,238	812,464	839,102	565,933	554,051
SPF Pacific Cod Capacity	23,807	35,643	34,934	39,681	39,597	21,171	10,863
DEA Pacific Cod Capacity	22,663	30,617	32,536	32,273	34,684	16,302	7,552
SPF Flatfish Capacity	50,889	60,168	59,697	54,540	38,200	25,157	18,448
DEA Flatfish Capacity	48,625	51,386	58,393	50,014	31,039	26,147	15,116
Days at Sea (vessel-days)	3,609	3,418	3,449	2,830	3,166	2,030	2,232
Tow Duration (hours)	47,132	39,715	42,947	35,545	38,414	21,373	25,692
Crew (man-weeks)	52,021	51,297	55,382	47,275	50,911	34,787	37,529
Registered Tonnage	42,512	42,252	41,355	41,355	41,621	29,331	27,181
Length (feet)	7,743	7,743	7,519	7,519	7,553	4,817	4,539
Horsepower	149,670	146,795	142,895	145,820	147,020	97,220	91,920

Table 4. Comparisons of Average Values Among AFA Ineligible and Eligible Vessels, 1994-1998

	AFA Ineligible	AFA Eligible
SPF $D_o(x,y)$ (Efficiency)	0.744	0.845
DEA $D_o(x,y)$ (Efficiency)	0.742	0.872
SPF Capacity Utilization	0.782	0.817
DEA Capacity Utilization	0.808	0.834
% of Vessels with Meal Plants	10%	60%
Pollock Catch	15,287	24,086
Pacific Cod Catch	1,178	555
Flatfish Catch	623	1,411
Days at Sea (vessel-days)	115	115
Tow Duration (hours)	1,461	1,371
Crew (man-weeks)	1,612	1,899
Registered Tonnage	670	1,736
Length (feet)	217	278
Horsepower	3,939	5,500

Table 5. Average Values Among Non-Idled AFA-Eligible Vessels, 1994-2000

	1994	1995	1996	1997	1998	1999	2000
SPF $D_o(x,y)$ (Efficiency)	0.864	0.875	0.890	0.892	0.873	0.883	0.892
DEA $D_o(x,y)$ (Efficiency)	0.853	0.871	0.882	0.960	0.922	0.854	0.935
SPF Capacity Utilization	0.750	0.845	0.858	0.813	0.835	0.893	0.930
DEA Capacity Utilization	0.741	0.820	0.870	0.879	0.902	0.891	0.934
Pollock Catch	26,487	26,340	25,028	25,914	25,104	26,864	32,252
Pacific Cod Catch	298	420	533	770	649	642	214
Flatfish Catch	945	1,361	2,251	1,231	1,303	927	960
Days at Sea (vessel-days)	111	115	119	95	111	127	144
Tow Duration (hours)	1,380	1,342	1,473	1,186	1,367	1,372	1,665
Crew (man-weeks)	1,813	2,009	2,125	1,783	1,959	2,208	2,457
Registered Tonnage	1,783	1,766	1,766	1,766	1,766	1,766	1,766
Length (feet)	283	283	283	283	283	283	283
Horsepower	5,831	5,640	5,640	5,835	5,835	5,835	5,835

Table 6. Comparison of Averages Among AFA-Eligible/Idled and AFA-Eligible/Active Vessels 1994-1998

	AFA-Eligible/Idled	AFA-Eligible/Active
SPF $D_o(x,y)$ (Efficiency)	0.761	0.864
DEA $D_o(x,y)$ (Efficiency)	0.783	0.891
SPF Capacity Utilization	0.677	0.847
DEA Capacity Utilization	0.710	0.861
% of Vessels with Meal Plants	20%	70%
Pollock Catch	16,229	25,770
Pacific Cod Catch	198	631
Flatfish Catch	2,306	1,219
Days at Sea (vessel-days)	113	116
Tow Duration (hours)	1,368	1,372
Crew (man-weeks)	1,447	1,996
Registered Tonnage	1,900	1,701
Length (feet)	254	284
Horsepower	4,604	5,692

Table 7. Logit Models of AFA-Eligible/AFA-Ineligible and Idled/Active Status

Eligible vs. Ineligible

Number Obs.= 147 | % Correct Predictions = 0.782 | R-squared = 0.253

Parameter	Estimate	Standard Error	T-Statistic	P-value	∂Prob./∂x_i
α	-1.770	1.200	-1.473	0.140	-0.282
$\alpha_{\text{meal plant}}$	2.242	0.576	3.890	0.000	0.357
β_{CU}	-0.483	1.241	-0.389	0.697	-0.077
β_{Do}	2.860	1.331	2.147	0.032	0.455

Eligible-Active vs. Eligible-Idled

Number Obs.= 103 | % Correct Predictions = 0.845 | R-squared = 0.373

Parameter	Estimate	Standard Error	T-Statistic	P-value	∂Prob./∂x_i
α	-5.233	1.900	-2.754	0.006	-0.644
$\alpha_{\text{meal plant}}$	2.894	0.693	4.171	0.000	0.356
β_{CU}	4.147	1.836	2.258	0.024	0.511
β_{Do}	1.879	1.749	1.073	0.283	0.231

Eligible-Active vs. Eligible-Idled -- Company 1

Number Obs.= 35 | % Correct Predictions = 0.829 | R-squared = 0.585

Parameter	Estimate	Standard Error	T-Statistic	P-value	∂Prob./∂x_i
α	-50.869	22.872	-2.224	0.026	-4.819
β_{CU}	41.247	18.949	2.176	0.030	3.908
β_{Do}	21.482	10.334	2.078	0.038	2.035

Eligible-Active vs. Eligible-Idled -- Company 2

Number Obs.= 23 | % Correct Predictions = 0.739 | R-squared = 0.370

Parameter	Estimate	Standard Error	T-Statistic	P-value	∂Prob./∂x_i
α	-10.396	4.603	-2.258	0.024	-1.661
β_{CU}	4.426	3.983	1.110	0.267	0.707
β_{Do}	9.222	3.926	2.348	0.019	1.474

Table 8. Hypothesis Tests from Second-Stage DEA Tobit Regressions

	Test Statistic	Standard Error	T-Ratio	P-Value	Conclusion
H_0: $TE_{elig} - TE_{inelig} = 0$	0.144	0.033	-4.271	0.000	Reject
H_0: $CU_{elig} - CU_{inelig} = 0$	0.002	0.032	-0.062	0.950	Fail to Reject
H_0: $TE_{elig,\ post\text{-}AFA} - TE_{elig,pre\text{-}AFA} = 0$	-0.011	0.033	0.338	0.735	Fail to Reject
H_0: $CU_{elig,\ post\text{-}AFA} - CU_{elig,pre\text{-}AFA} = 0$	0.079	0.032	-2.451	0.014	Reject
H_0: $TE_{elig,\ active} - TE_{elig,\ idled} = 0$	0.143	0.039	-3.619	0.000	Reject
H_0: $CU_{elig,\ active} - CU_{elig,\ idled} = 0$	0.105	0.039	-2.700	0.007	Reject
H_0: $TE_{meal\ plant} - TE_{no\ meal\ plant} = 0$	0.083	0.030	-2.712	0.007	Reject
H_0: $CU_{meal\ plant} - CU_{no\ meal\ plant} = 0$	0.004	0.031	-0.127	0.899	Fail to Reject
H_0: $TE_{company\ 1,active} - TE_{company\ 1,idled} = 0$	0.126	0.042	2.981	0.003	Reject
H_0: $CU_{company\ 1,active} - CU_{company\ 1,idled} = 0$	0.107	0.030	3.539	0.000	Reject
H_0: $TE_{company\ 2,active} - TE_{company\ 2,idled} = 0$	0.219	0.078	2.802	0.005	Reject
H_0: $CU_{company\ 2,active} - CU_{company\ 2,idled} = 0$	0.034	0.073	0.467	0.640	Fail to Reject

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Non-Technical Appendix

Although this is a technical working paper, it is also part of a public document that will be read by an audience with widely ranging backgrounds. In order to make the technical aspects of the capacity, CU, and TE estimation more accessible to all readers, the following discussion provides a less detailed, more intuitive description of the methods that underlie the empirical application to the pollock catcher-processor fleet.

The general methodology behind the methods used here is to represent the relationship between inputs used in harvesting, the stock of fish, and the resulting catch levels. Once this relationship has been estimated, one can then say something about how catch levels would change if fishing effort (variable input use) or harvesting efficiency increased. Because the focus is to estimate the fishing *capacity* of the fleet (and observed how it changed after the AFA was implemented), the techniques chosen to characterize production relationships are different than the commonly employed "production function."

Specifically, rather than looking at *average* relationships among inputs, stocks, and catch, (as a production function does), this paper examines the observed "*best-practice*" technology[27] -- generating a production frontier that represents the largest catch levels obtainable from a given level of inputs and fish stocks. By constructing such a frontier one is able to not only characterize the relationship between inputs and catch, but also make comparisons between the observations on the frontier and those for which less catch was generated (from the same level of inputs). These comparisons generate relative technical efficiency (TE) measures, in which those who have used the least amount of inputs or effort to obtain a particular level of catch are considered the most efficient, and those exerting greater levels (yet catching the same amount) are considered less efficient.

Two commonly used methods for estimating frontier relationships are data envelopment analysis (DEA) and the stochastic production frontier (SPF) model. DEA uses linear programming techniques to develop a representation of the frontier, while SPF uses econometric methods to estimate an equation representing the frontier. Regardless of the method employed, once the frontier is estimated each vessel's observed catch and effort level can be compared to

[27] This step is only the first part of estimating capacity. The second step involves examining how the best-practice catch would increase with increased levels of fishing effort (as will be described next).

the best-practice catch, and the potential increase in output is computed – showing how catch would increase if the observed production inefficiency was eliminated.

The next step in estimating capacity is to determine the extent to which catch would change if fishing effort was also increased. This is accomplished in the DEA and SPF models by shifting up the frontier in response to a hypothetical increase in the level of fishing effort (represented in this paper by days at sea, tow duration, and crew size). These increases in fishing effort can be thought of as increase in capacity utilization (CU), as more variable inputs are being combined with the given capital stock. In this analysis, the increase in effort levels used to generate capacity estimates was based on the highest levels exhibited by vessels of a similar size over the span of the data[28]. Some vessels' typical effort levels were near the maximum for their size class – indicating high levels of CU – while others' were much lower than the maximum (implying lower CU for these vessels). The values of CU (and TE) are discussed in the paper for different groups and time periods.

The final step in computing the capacity estimates was to scale up the observed catch levels for each vessel (for each species) to reflect the potential gains in TE and CU implied in the frontier models. Capacity estimates for the pollock catcher-processor fleet as a whole were computed by summing the species-specific capacity estimates for each individual vessel. See the discussion of the model results on pages 14-23 for further details.

[28] One could instead insert purely hypothetical levels – perhaps greater than levels ever observed – but the resulting capacity estimates would likely bear little resemblance to anything that would ever be caught in the fishery.